Quantitative Portfolio Management Strategy Based on the Combination of Mean-Variance Optimization and Time-Series Momentum

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Abstract. As financial market complexity increases, the need for effective and reliable quantitative portfolio management strategies has become more pressing. This study integrates Mean-Variance Optimization (MVO) with Time-Series Momentum (TSM) to create a hybrid strategy aimed at dynamically adjusting portfolio weights and improving overall performance. By leveraging historical stock data, the strategy was rigorously evaluated through in-sample testing (2010–2019) and out-of-sample testing (2019–2024). The findings reveal remarkable enhancements in cumulative returns, achieving 800% in-sample and 650% out-of-sample, underscoring the approach's robustness across varying market conditions. Additionally, risk metrics illustrate a delicate balance between long-term stability and short-term adaptability, offering insights into the strategy's effectiveness. However, elevated drawdowns and increased volatility in the out-of-sample phase raise concerns about potential overfitting and warrant further refinement. This study highlights the potential of combining MVO and TSM to enhance portfolio management by capitalizing on market trends while maintaining risk control. Future research could explore the incorporation of machine learning algorithms or alternative momentum signals to optimize performance further and address the challenges of adapting to diverse and evolving market environments.

Keywords: Investment Strategy, Financial Market, Asset Allocation, Risk Management.

1. Introduction

In recent years, driven by technological advancement and the integration of the global economy, the financial market has become increasingly complex. These changes motivate the prospect of quantitative portfolio management strategies.

For investors, pursuing stable and considerable returns while managing the risk under a controllable standard has become a significant need. Traditional investment approaches often struggle to deal with the challenges in the volatile markets and shifting economic conditions. Consequently, quantitative portfolio management strategies have provided an efficient tool for investors to construct robust portfolios.

Portfolio management is the core of modern investment theory. It is a foundation for optimizing asset allocation and balancing the trade-offs between risk and return. Within this context, the combination of Mean-Variance Optimization (MVO) and Time-Series Momentum (TSM) can provide a promising opportunity to improve investment outcomes while maintaining efficient risk management. This study explores the synergy between these two methodologies, offering a comprehensive framework to navigate the complexities of portfolio management.

2. Literature Review

2.1. Mean-Variance Optimization

Mean-Variance Optimization (MVO) was introduced by Markowitz in 1952, which is the footstone of modern portfolio theory. He created a groundbreaking strategy and built the foundation for quantitative portfolio management using a mathematical framework to balance risk and return through optimal asset allocation [1]. MVO allows investors to construct efficient portfolios to maximize expected returns under a given risk level or achieve a target return with the minimum risk level. This innovation has fundamentally changed investment practices by shifting the focus from the risk of individual assets to the risk of the entire portfolio [2]. Although MVO has a promising performance under a theoretical foundation, it has several challenges. The strategy shows high sensitivity to small changes in input parameters, such as expected returns and the covariance matrix of asset returns. This sensitivity can result in significant instability in portfolio weights, frequent rebalancing, and high transaction costs, negatively influencing portfolio performance [3].

2.2. Time-Series Momentum

Researchers introduced new strategies to enhance portfolio robustness and adaptability to address these limitations. According to the research by Berger & Fieberg, alternative estimation techniques are considered to improve the robustness of MVO [4]. Time-Series Momentum is an effective strategy. TSM offers a dynamic approach to portfolio management and predicts future movements based on historical price trends, which capitalizes on the tendency of asset prices to exhibit positive autocorrelation over time. Empirical studies have demonstrated the effectiveness of TSM across various asset categories, including equities, commodities, and fixed income, as well as its resilience in different market conditions [1]. By combining momentum signals, TSM provides actionable insights for portfolio adjustment. Thus, by introducing TSM to MVO, MVO's performance has enhanced under volatile market conditions [3].

2.3. The Combination of MVO and TSM

The combination of MVO and TSM represents a promising direction in quantitative portfolio management. The integration involves using the sensitivity of MVO to static inputs and adjusting it by TSM's trend signals [5]. It also incorporates MVO's diversification into TSM's focus on short-term movements [6, 7].

This integrated approach highlights the strengths of both strategies. The MVO performs well in long-term optimization, and the TSM emphasizes adaptation to the dynamic environment. By integrating these two strategies, investors can create portfolios that are not only theoretically sound but also more stable and diverse by using MVO and more adaptable to the real-world market with TSM [8, 9].

2.4. Evaluation Metrics

The method sets evaluation indicators to evaluate the overall strategy. The method uses the Sharpe Ratio to measure risk-adjusted returns by various portfolio management [8, 10]. Maximum Drawdown provides decisions into downside risk by referring to the portfolio's most significant peak-to-trough decline [7, 9].

2.5. Research Gaps and Contributions

Although the strategies of MVO and TSM have been studied separately, the combination of these strategies has not been explored widely [8, 11]. Nevertheless, some researchers have practically implemented the integration of these strategies by applying them to dynamic market conditions and using back-testing [5, 6].

This essay aims to fill these gaps by combining MVO and TSM into a robust framework and evaluating its performance through back-testing on historical market data [5, 11].

3. Methods

The Portfolio optimization and evaluation process involves several steps, including data collection, data cleaning, portfolio optimization, momentum strategy application, and portfolio evaluation. The process combines Mean-Variance Optimization (MVO) and Time Series Momentum (TSM), creating an optimal portfolio and evaluating the results.

3.1. Data Collection

The project chooses stocks from different industries, including technology, finance, consumer, healthcare, and energy. The in-sample data collected stocks' prices from 2010.1.1 to 2018. 12.23 from Yahoo Finance after being adjusted by considering dividends, stock splits, and other factors to reflect the actual performance of these stocks. The data was used to calculate the daily return, annual volatility, annual average return, and risk-return ratio to screen for the top 15 best-performing stocks (see Table 1).

Table 1. Screened Stocks.

Number	Stocks Symbol	Company
1	ABT	Abbott Laboratories
2	ADBE	Adobe Inc.
3	AMZN	Amazon.com, Inc.
4	COST	Costco Wholesale Corporation
5	CRM	Salesforce, Inc.
6	CSCO	Cisco Systems, Inc.
7	ISRG	Intuitive Surgical, Inc.
8	LLY	Eli Lilly and Company
9	MA	Mastercard Incorporated
10	MSFT	Microsoft Corporation
11	NEE	NextEra Energy, Inc
12	NKE	Nike, Inc.
13	PFE	Pfizer Inc.
14	TJX	The TJX Companies, Inc
15	UNH	UnitedHealth Group Incorporated

The process cleans the data for the 15 stocks selected, fills in the missing values, and calculates the daily return, average return, and covariance matrix. Then, construct an equal-weight portfolio. The portfolio's annualized expected return is 21.00%, with a volatility of 15.40%, representing a well-balanced risk-return profile.

3.2. Portfolio Optimization and Momentum Strategy

Mean-Variance Optimization (MVO). This project uses a mean-variance optimization (MVO) strategy to find the best weights for each stock to maximize the Sharpe ratio and get higher returns at the same risk level. The process initially calculates the risk-free rate for calculating the Sharpe ratio. Next, it defines functions to calculate portfolio volatility and Sharpe ratio. Using SciPy's tools, the code calculates an initial set of optimal weights. Additionally, it includes a momentum factor to refine the portfolio further, adjusting based on average returns from the past 90 days to capture recent trends. The process sets the stock's weight (1% to 25%). The portfolio results show a significant portion of allocation to stocks like ADBE and ISRG (getting over 24%) and ABT and MA (getting over 10%). In contrast, smaller portions go to other stocks for diversification (see Figure 1). This method effectively balances risk and return to maximize the portfolio's overall risk-adjusted return.

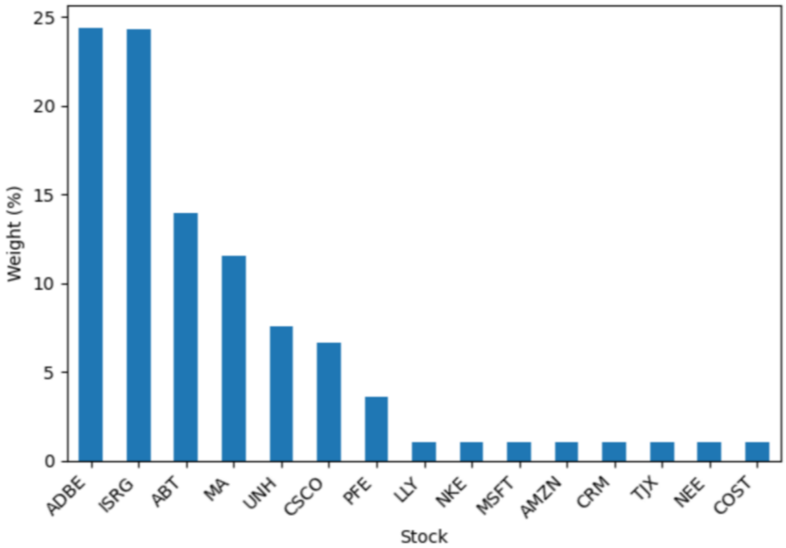

Figure 1. The Optimal Portfolio Weights Before Considering the Momentum.

Time-Series Momentum (TSM). Then, the project applies TSM to adjust the portfolio's stock weights for better performance. A 3-month (63 trading days) window was selected for momentum calculation because it balances capturing recent trends and avoiding outdated information. This 3-month period is long enough to smooth out any short-term fluctuations but still responsive enough to capture the current market trends. It strikes a good balance—short enough to avoid too much noise but long enough to reflect meaningful changes in price. It calculates momentum based on how each stock has performed over the past three months, which helps us identify buy and sell signals. Stocks showing positive momentum get a 40% increase in weight, while those with negative momentum see their weight reduced by 40%. It adjusts the weights once these changes are made, so the total portfolio still adds up to 100%. The code also factors in transaction costs due to these changes. The result shows that stocks like ADBE, ISRG, and ABT have higher allocations, while others hold smaller portions, maintaining a diversified portfolio and risk management. The final goal is to boost returns using recent momentum trends while keeping the risk level.

3.3. Evaluation of Transaction Cost

The project assumes a cost of 0.1% per transaction. After adjusting the portfolio weights, the weight change for each stock is calculated, and the total transaction cost is estimated accordingly (see Figure 2). Ultimately, transaction costs have less of an impact on the mix, with a total transaction cost of 0.000414 (i.e., 0.0414%).

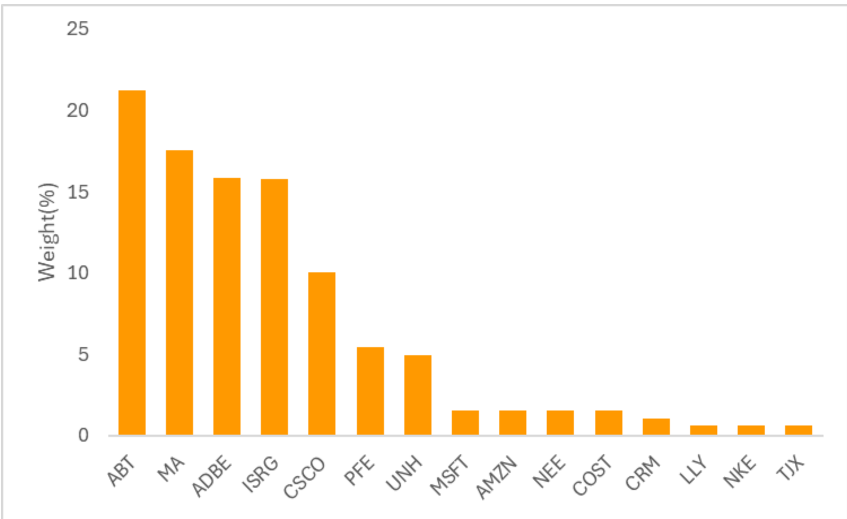

Figure 2. The Optimal Portfolio Weights After Considering the Momentum.

3.4. Portfolio Evaluation

• Cumulative return (see Figure 3): By calculating the cumulative product of daily returns, the cumulative return of the portfolio has gradually increased since 2010 and reached about 8 times by 2019, indicating that the portfolio performed well over the long term.

• Max Drawdown: To assess risk exposure, the process calculates the max Drawdown of the portfolio, and the result was -15.33%. This statistic shows the most significant risk the portfolio could face during the investment period, giving us an idea of its overall risk and volatility.

• As for the Sharpe ratio, the in-sample Sharpe ratio is 1.28, and after factoring in transaction costs, it is 1.25. This tells us that although the transaction cost slightly influences the Sharpe ratio, the overall Sharpe ratio is still at a decent level.

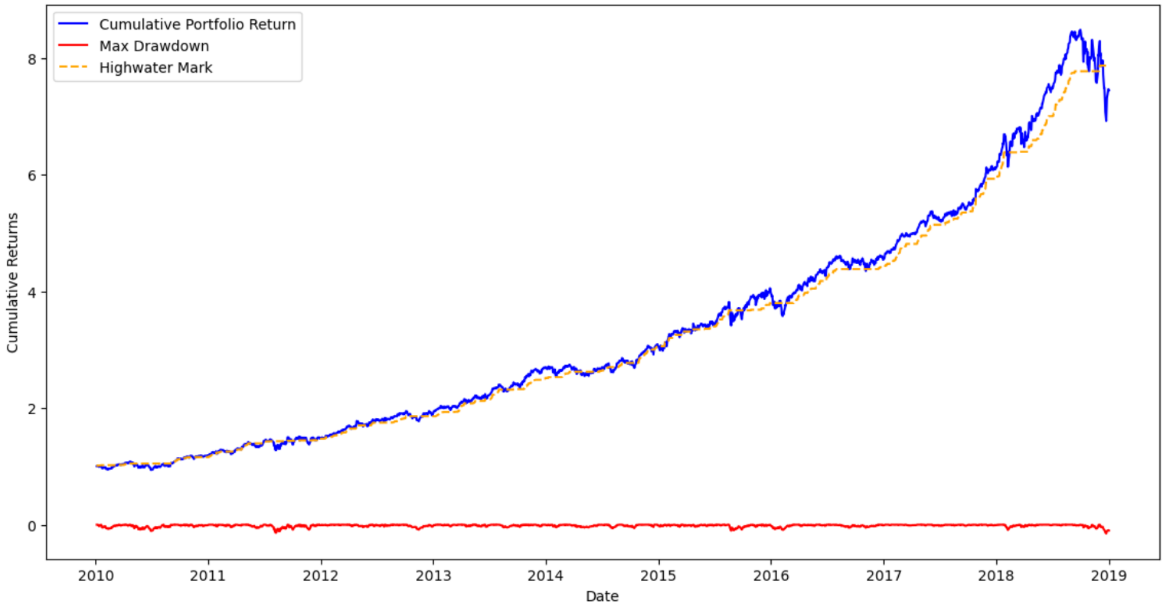

Figure 3. Portfolio Cumulative Return Performance and Risk Indicators.

3.5. In-Sample and Out-of-Sample Validation

To validate the robustness and universality of the strategy, the project further splits the dataset into in-sample and out-of-sample periods: data from 2010 to 2019 was used as in-sample data for training and parameter optimization, while data from 2019 to the end of 2024 was used for testing the model's effectiveness.

During training, the step optimizes portfolio weights to design a multi-factor strategy to maximize risk-adjusted returns. These weights were then tested on out-of-sample data. The results showed that the annualized returns slightly dropped during the out-of-sample phase, the Sharpe ratio dropped, and the maximum Drawdown increased, suggesting increased risk and overfitting. Additionally, the decrease in trading frequency was shown in the out-of-sample, leading to lower transaction costs and slippage and positively impacting overall performance.

4. Results

The results illustrate the performance of applying the MVO and TSM combination strategy, including analysis of portfolio weights, cumulative returns, risk metrics, trading frequency, and performance metrics. Eventually, the results also evaluate the in-sample performance compared with the out-of-sample periods. The findings further explore the strategy's ability to adapt to market dynamics while maintaining robust performance.

4.1. Portfolio Weights

The comparison of portfolio weights under MVO and adjusted after TSM emphasizes the dynamic nature of the MVO-TSM strategy (see Table 2).

Table 2. Comparison of Optimal Portfolio Weights.

Stocks Symbol	Original Weight (%)	Adjusted Weight (%)
ADBE	24.404675	15.881313
ISRG	24.267718	15.792189
ABT	13.973388	21.217386
MA	11.546094	17.531749
UNH	7.575761	4.929918
CSCO	6.628914	10.065434
PFE	3.603449	5.471527
LLY	1.000000	0.650749
NKE	1.000000	0.650749
MSFT	1.000000	1.518414
AMZN	1.000000	1.518414
CRM	1.000000	1.084681
TJX	1.000000	0.650749
NEE	1.000000	1.518414
COST	1.000000	1.518414

The portfolio considers weights based on the historical Sharpe ratios and volatility. It allocated heavy weights to stocks with a higher Sharpe ratio and lower volatility. Stocks like ADBE (24.40%) and ISRG (24.27%) show a large proportion. ABT (13.97%) and MA (11.55%) are allocated with moderate weights. Nevertheless, minimal weights (1%) were allocated to stocks such as LLY, NKE, and MSFT to maintain diversification while limiting risk exposure.

After combining TSM with a 3-month momentum window, the results considerably changed. Stocks with stronger momentum recently, like ABT and MA weights, increased to 1.22% and 17.53%, respectively. In contrast, stocks with smaller momentum, like ADBE and ISRG weights, decreased to 15.88% and 15.79%. CSCO stock weights showed positive trends, which increased from 6.62% to 10.06%.

The results before and after adjustments illustrate that the portfolio's responsiveness to recent market trends was improved through the TSM adjustments, which allocated more weight to stocks with stronger short-term momentum. Smaller weights were given to riskier assets to reduce concentration risk, ensuring diversification was maintained.

4.2. Cumulative Returns

According to Figure 4, the cumulative return performance of the portfolio is compared by the in-sample (2010–2019) and out-of-sample (2019–2024) periods.

The results demonstrated a strong performance in the in-sample period. The cumulative returns grew to about 800% by the end of 2019. Long-term risk-return trade-offs were optimized through MVO, while TSM captured short-term trends, especially in bullish markets, with stocks like ISRG and ADBE playing key roles in driving growth. Out-of-sample, the growth rate of cumulative returns slowed but remained positive, stabilizing near 650%. Despite higher market volatility, TSM helped reduce losses during downturns, such as the 2022 market dip, by allocating more weight to momentum-driven stocks like ABT.

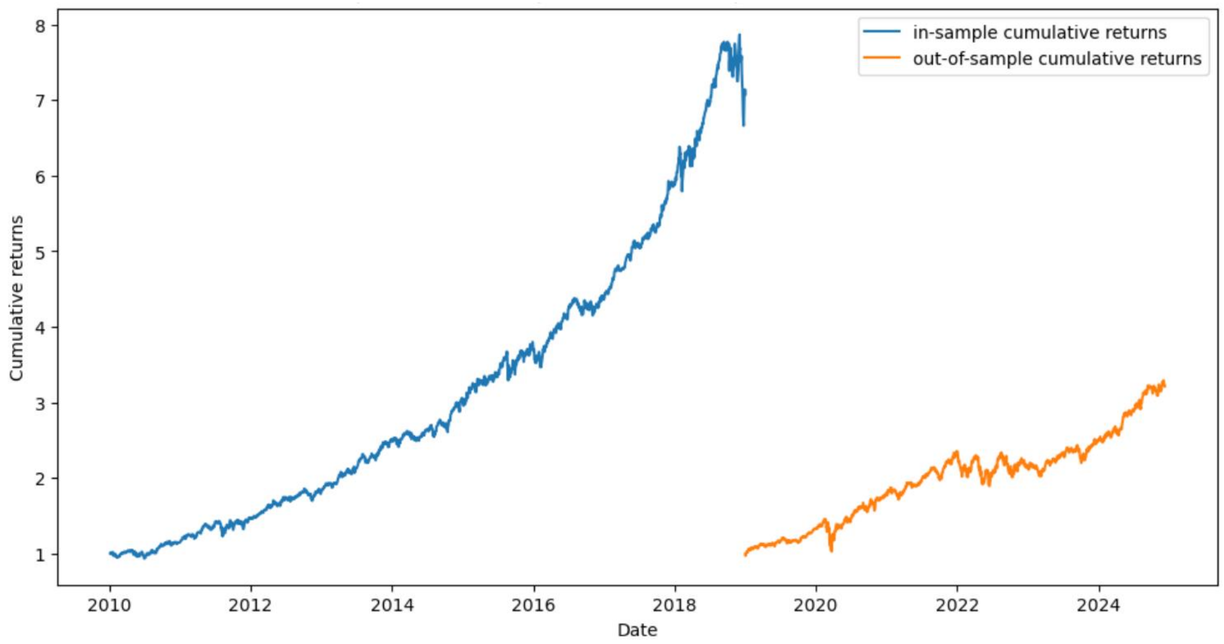

Figure 4. Comparison of In-sample and Out-of-sample Cumulative Returns.

Strong in-sample returns highlighted the effectiveness of the MVO and TSM combination, while out-of-sample results demonstrated the strategy's adaptability to real-world conditions.

4.3. Trading Frequency

Figure 5 compares the number of buy and sell signals during the in-sample and out-of-sample periods.

- In-Sample Signals: There were 8,354 buy signals and 24,566 sell signals, which shows a market with more selling activity.
- Out-of-Sample Signals: The number of buy and sell signals dropped to 5240 and 16,191, respectively, reflecting a decline in trading frequency.

In the out-of-sample periods, the trading frequency decreased, which suggests the portfolio's focus on maintaining returns while controlling costs. The decline trends also showed that the portfolio is adjusted to less favorable market conditions.

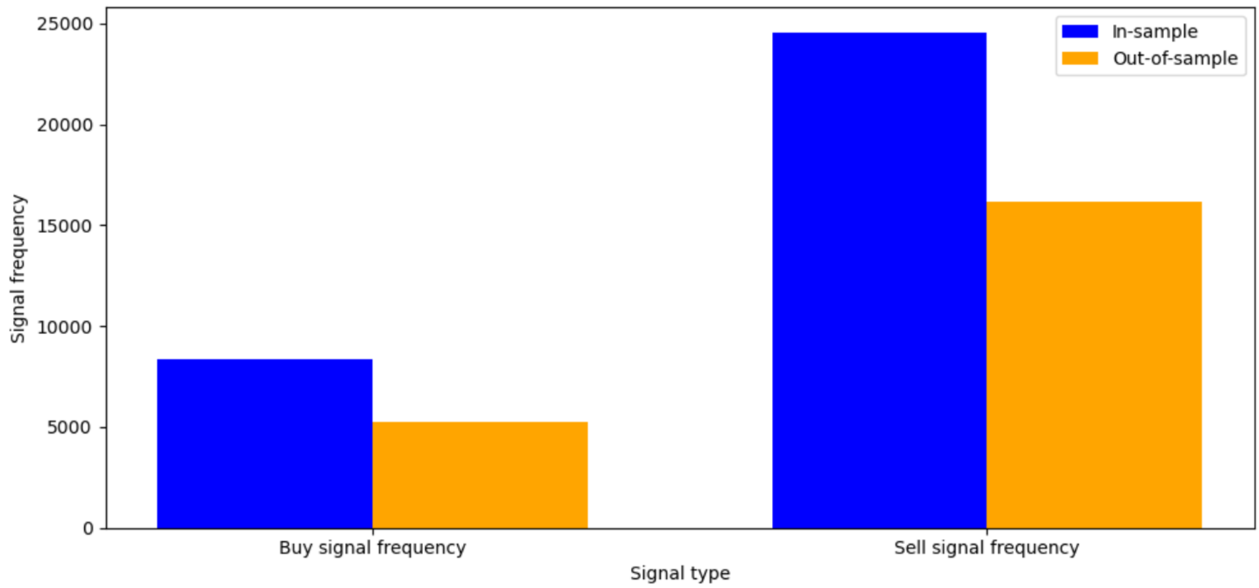

Figure 5. Comparison of the Number of In-sample and Out-of-sample Buy and Sell Signals.

4.4. Performance Metrics Calculation (After Adjusted)

Table 3 summarizes the statistics of the Sharpe ratio, maximum Drawdown, and annualized volatility in in-sample and out-of-sample periods.

Table 3. Compares In-Sample and Out-of-Sample Performance Metrics.

Metric	In-Sample	Out-of-Sample
Annualized Return (%)	22.83	21.68
Annualized Volatility (%)	14.44	19.98
Sharpe Ratio	1.28	0.87
Maximum Drawdown (%)	-15.33	-29.60

In the in-sample period, the portfolio performed well, with a Sharpe ratio of 1.28, a maximum drawdown of -15.33%, and annualized volatility of 14.44%, showing good risk-adjusted returns and controlled risk levels. The Sharpe ratio dropped to 0.87 out-of-sample, with a maximum drawdown of -29.60% and annualized volatility rising to 19.98%. The portfolio produced positive returns despite higher risks, demonstrating its resilience. However, the larger Drawdown may suggest overfitting during optimization, reflecting increased uncertainty and more significant market fluctuations.

The MVO and TSM strategy showed it could adapt by capturing short-term momentum while still focusing on long-term goals. It achieved strong cumulative returns during both in-sample and out-of-sample periods, with good risk-adjusted performance. Trading was more efficient due to lower frequency during testing, which helped reduce transaction costs. The results suggest that the approach is practical for portfolio management and could work well in real-world scenarios. Improvements like refining momentum signals or adding new factors might improve it.

5. Discussion

This study examines the effectiveness of combining mean-variance optimization (MVO) with time series momentum (TSM) in portfolio management.

The introduction of TSM addresses a limitation of MVO, which relies on static input and often performs poorly in dynamic markets. Incorporating momentum signals based on recent price trends makes the portfolio more responsive to market changes. For instance, stocks with strong momentum signals like ABT and MA gain higher weight. The adjustments keep the portfolio with the current market trends and maintain the diversification of MVO. This is consistent with previous research on the importance of momentum factors in portfolio performance [5].

The cumulative return results show that the combination strategy is effective. In the in-sample phase, the portfolio grows steadily, and in the out-of-sample phase, it is resilient in a volatile market. Despite a reduced growth rate in the testing phase due to challenges like increased volatility and potential model overfitting, the strategy maintains positive returns, demonstrating its practical applicability for investors seeking stable returns in an unpredictable market.

Risk indicators reveal trade-offs. During the in-sample periods, maximum Drawdown and volatility increased, which indicates greater risk. The rising risk suggests that investors need to be cautious when applying such a framework to a highly dynamic market. In the future, the project should add additional risk controls or optimize momentum signals to enhance portfolio resilience.

Trading frequency enhances the effectiveness of the integrated framework. The decline of the trading frequency in the out-of-sample periods aims to reduce transaction costs, which shows the portfolio's ability to adapt to adverse market conditions.

Overall, this study extends the application of integrating MVO and TSM. This study uses this integrated strategy to balance long-term stability while strengthening short-term adaptive portfolios. While the results are encouraging, future research could further explore integrating machine learning techniques or alternative momentum signals to optimize performance in different market environments.

6. Conclusion

This research aims to address portfolio management challenges in dynamic financial markets by integrating mean-variance optimization (MVO) and time series momentum (TSM). The results witness a significant improvement in portfolio performance. This improvement indicates that this hybrid strategy effectively combines the benefits of MVO's long-term stability with the short-term adaptability of TSM. During the in-sample periods, the cumulative return reached 800%. In the out-of-sample stage, the cumulative return is stable at 650%. The considerable statistics demonstrate the strategy's robustness in stable and volatile market conditions. Meanwhile, TSM reallocates more portfolio weights to momentum-driven stocks, improving its responsiveness to market trends. The reduction of transaction frequency in the out-of-sample periods aims to reduce transaction costs and further improve the overall efficiency of the strategy.

However, there are some limitations to this study. Reliance on historical stock data and assumptions, such as fixed transaction costs and three-month momentum Windows, may not fully reflect the complexity of the real market. In addition, the high retracement and volatility in the out-of-sample stage indicate that the strategy has overfitting and sensitivity in the case of high market volatility. Consequently, further improvements are needed.

In the future, research can introduce machine learning algorithms into the strategy to enhance portfolio adaptability. In addition, testing strategies on a broader dataset, including international markets and alternative asset classes, may also provide valuable insights. After solving these limitations, the strategy can contribute to this study to further optimize portfolio strategies for a diverse and complex market environment.

References

[1] Markowitz, H.: Modern portfolio theory. Journal of Finance, 7 (11), 77 - 91 (1952).

[2] Fabozzi, F. J., Markowitz, H. M., & Gupta, F.: Portfolio selection. The Theory and Practice of Investment Management, 45 - 78 (2011).

[3] Fague, J., & Almeida, C.: Robust optimization of time series momentum portfolios. Brazilian Review of Finance, 19 (1), 52 – 69 (2021).

[4] Berger, T., & Fieberg, C.: On portfolio optimization: Forecasting asset covariances and variances based on multi-scale risk models. The Journal of Risk Finance, 17 (3), 295 - 309 (2016).

[5] Moskowitz, T., Ooi, Y.H. and Pedersen, L.H.: Time series momentum. Journal of Financial Economics, 104: 228 – 250 (2012).

[6] Malandreniotis, D.: Probabilistic Forecasting Models for Multidimensional Financial Time-series With Applications to Systematic Portfolio Management (Doctoral dissertation, UCL (University College London)) (2024).

[7] Tadlaoui, G.: Intelligent Portfolio Construction: Machine-Learning enabled Mean-Variance Optimization (Doctoral dissertation, MA thesis. Master’s thesis, Imperial College London). (2017).

[8] Leivo, T. H., & Pätäri, E. J.: Enhancement of value portfolio performance using momentum and the long-short strategy: The Finnish evidence. Journal of Asset Management, 11, 401 - 416 (2011).

[9] Singh, P., Jha, M., Sharaf, M., El-Meligy, M. A., & Gadekallu, T. R.: Harnessing a hybrid CNN-LSTM model for portfolio performance: A case study on stock selection and optimization. Ieee Access, 11, 104000 - 104015 (2023).

[10] Huang, Y., Jia, Y., & Zhou, X. Y.: Mean-Variance Portfolio Selection by Continuous-Time Reinforcement Learning: Algorithms, Regret Analysis, and Empirical Study. arXiv preprint arXiv: 2412. 16175 (2024).

[11] Navarro, M. M., Young, M. N., Prasetyo, Y. T., & Taylar, J. V.: Stock market optimization amidst the COVID-19 pandemic: Technical analysis, K-means algorithm, and mean-variance model (TAKMV) approach. Heliyon, 9 (7) (2023).